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Integrating Neuromuscular and Touchscreen Input for Machine Control

ABSTRACT

Current touchscreen interfaces are unable to distinguish between individual fingers or to determine poses associated with the user's hand. This limits the use of touchscreens in recognizing user input. As discussed herein, a statistical model can be trained using training data that includes sensor readings known to be associated with various hand poses and gestures. The trained statistical model can be configured to determine arm, hand, and/or figure configurations and forces (e.g., handstates) based on sensor readings, e.g., obtained via a wearable device such as a wristband with wearable sensors. The statistical model can identify the input from the handstate detected by the wearable device. For example, the handstates can include identification of a portion of the hand that is interacting with the touchscreen, a user's finger position relative to the touchscreen, an identification of which finger or fingers of the user's hand are interacting with the touchscreen, etc. The handstates can be used to control any aspect(s) of the touchscreen or a connected device indirectly through the touchscreen.

KEYWORDS

- Neuromuscular input
- Touchscreen input
- Gesture recognition
- Handstate
- Hand pose
- EMG sensor
- Labeled gestures
- Multiuser touchscreen
- Wristband
- Wearable device
- Machine learning
- Statistical model

BACKGROUND

In some computer touchscreen control applications, it is desirable for the application to be able to determine additional information about the touchscreen interaction to further enhance the accuracy and/or sophistication of the computer application control via the touchscreen interaction by a user. For example, in a computer application that uses a touchscreen as a means of control, determining which part of a user's body (e.g., fingers of a hand) is touching the touchscreen cannot be easily determined by the touchscreen itself but would be beneficial for enhancing the quality or sophistication of control.

In some touchscreen interactions, multiple users may collaborate by concurrently touching the touchscreen but the touchscreen is generally not able to distinguish two fingers from one user from a pair of fingers composed of one finger from each of two users. The limitation of a touchscreen to distinguish which user is interacting with it limits the functionality of touchscreen control by the collaborating users.

DESCRIPTION

All or portions of the human musculoskeletal system can be modeled as a multi-segment articulated rigid body system, with joints forming the interfaces between the different segments and joint angles defining the spatial relationships between connected segments in the model. Constraints on the movement at the joints are governed by the type of joint connecting the segments and the biological structures (e.g., muscles, tendons, ligaments) that restrict the range of movement at the joint. For example, the shoulder joint connecting the upper arm to the torso and the hip joint connecting the upper leg to the torso are ball and socket joints that permit extension and flexion movements as well as rotational movements. By contrast, the elbow joint connecting the upper arm and the forearm and the knee joint connecting the upper leg and the

lower leg allow for a more limited range of motion.

As described herein, a multi-segment articulated rigid body system is used to model portions of the human musculoskeletal system. However, it should be appreciated that some segments of the human musculoskeletal system (e.g., the forearm), though approximated as a rigid body in the articulated rigid body system, may include multiple rigid structures (e.g., the ulna and radius bones of the forearm) that provide for more complex movement within the segment that is not explicitly considered by the rigid body model. Accordingly, a model of an articulated rigid body system for use with the technology described herein includes segments that represent a combination of body parts that are not strictly rigid bodies.

In kinematics, rigid bodies are objects that exhibit various attributes of motion (e.g., position, orientation, angular velocity, acceleration). Knowing the motion attributes of one segment of the rigid body enables the motion attributes for other segments of the rigid body to be determined based on constraints in how the segments are connected. For example, the hand may be modeled as a multi-segment articulated body with the joints in the wrist and each finger forming the interfaces between the multiple segments in the model. Movements of the segments in the rigid body model can be simulated as an articulated rigid body system in which position (e.g., actual position, relative position, or orientation) information of a segment relative to other segments in the model are predicted using a trained statistical model, as described in more detail below.

The portion of the human body approximated by a musculoskeletal representation as described herein, as an example, is a hand or a combination of a hand with one or more arm segments. The information used to describe a current state of the positional relationships between segments and force relationships for individual segments or combinations of segments in the

musculoskeletal representation is referred to herein as the handstate of the musculoskeletal representation. However, that the techniques described herein are also applicable to musculoskeletal representations of portions of the body other than the hand such as an arm, a leg, a foot, a torso, a neck, or any combination of the foregoing.

In addition to spatial (e.g., position/orientation) information, the described techniques can predict force information associated with one or more segments of the musculoskeletal representation. For example, linear forces or rotational (torque) forces exerted by one or more segments may be estimated. An example of linear forces is the force of a finger or hand pressing on a solid object such as a table, and a force exerted when two segments (e.g., two fingers) are pinched together. An example of rotational forces is rotational forces that are created when segments in the wrist or fingers are twisted or flexed. Per techniques described herein, the force information determined as a portion of a current handstate estimate includes one or more of pinching force information, grasping force information, or information about co-contraction forces between muscles represented by the musculoskeletal representation.

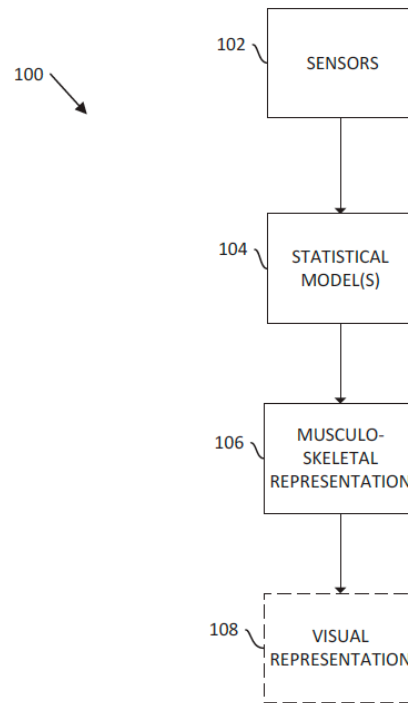
**Fig. 1**

FIG. 1 is a schematic diagram of a computer-based system (100) for reconstructing handstate information. The system includes a plurality of sensors (102) configured to record signals resulting from the movement of portions of a human body. The sensors may include autonomous sensors. As used herein, the term “autonomous sensors” refers to sensors configured to measure the movement of body segments without requiring the use of external devices. The sensors may also include non-autonomous sensors in combination with autonomous sensors. As used herein, the term “non-autonomous sensors” refers to sensors configured to measure the movement of body segments using external devices. Some examples of external sensors used in non-autonomous sensors include wearable (e.g. body-mounted) cameras, global positioning systems, or laser scanning systems.

Autonomous sensors may include a plurality of neuromuscular sensors configured to record signals arising from neuromuscular activity in skeletal muscle of a human body. The term

“neuromuscular activity” as used herein refers to neural activation of spinal motor neurons that innervate a muscle, muscle activation, muscle contraction, or any combination of the neural activation, muscle activation, and muscle contraction. Neuromuscular sensors may include one or more electromyography (EMG) sensors, one or more mechanomyography (MMG) sensors, one or more sonomyography (SMG) sensors, a combination of two or more types of EMG sensors, MMG sensors, and SMG sensors, and/or one or more sensors of any suitable type that are configured to detect nervous signals, muscular signals, and/or neuromuscular signals. The neuromuscular sensors may be used to sense muscular activity related to a movement of the part of the body controlled by muscles from which the neuromuscular sensors are arranged to sense the muscle activity. Spatial information (e.g., position and/or orientation information) and force information describing the movement may be predicted based on the sensed neuromuscular signals as the user moves over time.

Autonomous sensors may include one or more Inertial Measurement Units (IMUs), which measure a combination of physical aspects of motion, using, for example, an accelerometer, a gyroscope, a magnetometer, or any combination. IMUs may be used to sense information about the movement of the part of the body on which the IMU is attached and information derived from the sensed data (e.g., position and/or orientation information) may be tracked as the user moves over time. For example, IMUs may be used to track movements of portions of a user’s body proximal to the user’s torso relative to the sensor (e.g., arms, legs) as the user moves over time.

In configurations that include at least one IMU and multiple other neuromuscular sensors, the IMU(s) and neuromuscular sensors may be arranged to detect movement of different parts of the human body. For example, the IMU(s) may be arranged to detect movements of one or more

body segments proximal to the torso (e.g., an upper arm), whereas the neuromuscular sensors may be arranged to detect movements of one or more body segments distal to the torso (e.g., a forearm or wrist).

The techniques described herein are not limited based on the particular sensor arrangement. In an example configuration, at least one IMU and multiple neuromuscular sensors may be co-located on a body segment to track movements of body segment using different types of measurements. In one implementation described in more detail below, an IMU sensor and a plurality of neuromuscular sensors are arranged on a wearable device configured to be worn around the lower arm or wrist of a user. In such an arrangement, the IMU sensor is configured to track movement information (e.g., positioning and/or orientation over time) associated with one or more arm segments, to determine, for example whether the user has raised or lowered their arm, whereas the neuromuscular sensors are configured to determine movement information associated with wrist or hand segments to determine, for example, whether the user has an open or closed hand configuration.

Each of the autonomous sensors includes sensing components configured to sense information about a user. In the case of IMUs, the sensing components include one or more accelerometers, gyroscopes, magnetometers, or a combination. The sensing components are configured to measure characteristics of body motion, e.g., acceleration, angular velocity, and sensed magnetic field around the body. In the case of neuromuscular sensors, the sensing components include, e.g., electrodes configured to detect electric potentials on the surface of the body (e.g., for EMG sensors) vibration sensors configured to measure skin surface vibrations (e.g., for MMG sensors), and acoustic sensing components configured to measure ultrasound signals (e.g., for SMG sensors) arising from muscle activity.

The output of one or more of the sensing components is processed using hardware signal processing circuitry (e.g., to perform amplification, filtering, and/or rectification). In some configurations, a portion of signal processing of the output of the sensing components is performed in software. In general, signal processing of autonomous signals recorded by the autonomous sensors can be performed in hardware and/or software.

The recorded sensor data are processed to compute additional derived measurements that are then provided as input to a statistical model, as described in more detail below. For example, recorded signals from an IMU sensor can be processed to derive an orientation signal that specifies the orientation of a rigid body segment over time. Autonomous sensors can implement signal processing using components integrated with the sensing components. Alternatively, a portion of the signal processing can be performed by components in communication with, but not directly integrated with the sensing components of the autonomous sensors.

In some configurations, a subset of autonomous sensors are arranged as a portion of a wearable device configured to be worn on or around part of a user's body. In an example, an IMU sensor and a plurality of neuromuscular sensors are arranged circumferentially around an adjustable and/or elastic band such as a wristband or armband configured to be worn around a user's wrist or arm. Alternatively, some of the autonomous sensors can be arranged on a wearable patch configured to be affixed to a portion of the user's body. In another example, multiple wearable devices, each having one or more IMUs and/or neuromuscular sensors included thereon can be used to predict musculoskeletal position information for movements that involve multiple parts of the body.

In different configurations, the sensors can include neuromuscular sensors (e.g., EMG sensors) only, or neuromuscular sensors and at least one "auxiliary" sensor configured to

continuously record a plurality of auxiliary signals. Examples of auxiliary sensors include other autonomous sensors such as IMU sensors, and non-autonomous sensors such as an imaging device (e.g., a camera), a radiation-based sensor for use with a radiation-generation device (e.g., a laser-scanning device), or other types of sensors such as a heart-rate monitor.

The system also includes one or more computer processors (not shown in FIG. 1) programmed to communicate with sensors 102. For example, signals recorded by one or more of the sensors may be provided to the processor(s), which is programmed to execute machine learning algorithms that process signals output by the sensors to train statistical models (104), and the trained (or retrained) statistical model(s) 104 may be stored for later use in generating a musculoskeletal representation (106). Some examples of statistical models that may be used to predict handstate information based on recorded signals from sensors 102 are discussed in detail below.

The system also optionally includes a display controller configured to display a visual representation (108), e.g., of a hand. As discussed in more detail below, computer processors are used to implement trained statistical model(s) configured to predict handstate information based on signals recorded by the sensors. The predicted handstate information is used to update the musculoskeletal representation, which is then optionally used to render a visual representation based on the updated musculoskeletal representation incorporating the current handstate information. Real-time reconstruction of the current handstate and subsequent rendering of the visual representation reflecting the current handstate information in the musculoskeletal model provides visual feedback to the user about the effectiveness of the trained statistical model to accurately represent an intended handstate. In another example, a metric associated with a musculoskeletal representation (e.g., a likelihood metric for one or more hand gestures or a

quality metric that represents a confidence level of estimating a position, movement, or force of a segment of a multi-segment articulated rigid body system such as a hand) can be provided to the user or other third-party.

A statistical model is used for predicting musculoskeletal information based on signals recorded from wearable autonomous sensors. The statistical model may be used to predict the musculoskeletal position information without having to place sensors on each segment of the rigid body that is to be represented in the computer-generated musculoskeletal representation. The types of joints between segments in a multi-segment articulated rigid body model constrain movement of the rigid body. Additionally, different individuals tend to move in characteristic ways when performing a task that can be captured in statistical patterns of individual user behavior.

Some of these constraints on human body movement can be explicitly incorporated into statistical models used for prediction. Additionally, or alternatively, the constraints can be learned by the statistical model through training based on recorded sensor data. Constraints imposed in the construction of the statistical model are those set by anatomy and the physics of a user's body, while constraints derived from statistical patterns are those set by human behavior for one or more users from which sensor measurements are measured. The constraints may comprise part of the statistical model itself being represented by information (e.g., connection weights between nodes) in the model.

A statistical model can also be used for predicting handstate information to enable the generation and/or real-time update of a computer-based musculoskeletal representation. The statistical model may be used to predict the handstate information based on IMU signals, neuromuscular signals (e.g., EMG, MMG, and SMG signals), external device signals (e.g.,

camera or laser-scanning signals), or a combination signals that are detected as a user performs one or more movements.

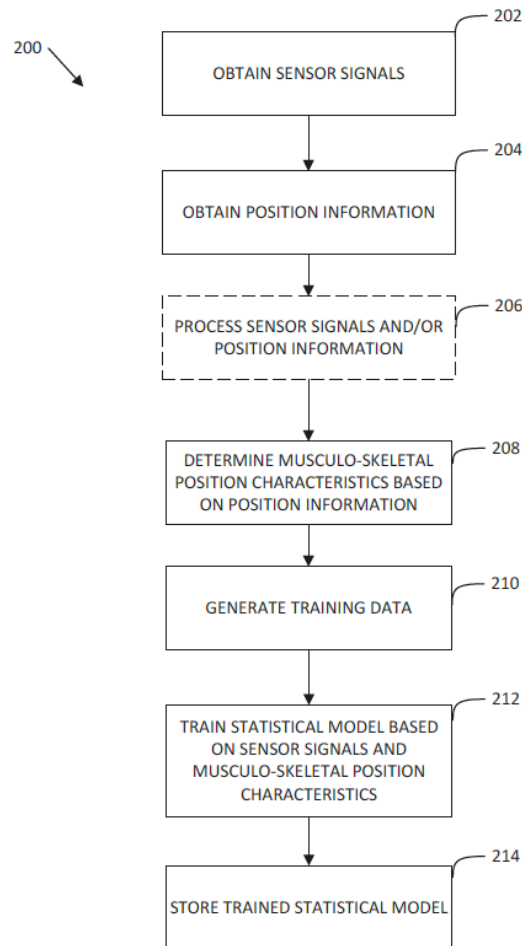


Fig. 2

FIG. 2 is a flowchart of an example process (200) for generating (also referred to as training) a statistical model for predicting musculoskeletal position information using signals recorded from sensors. The training process can be executed by any suitable computing device(s). For example, process 200 can be executed by computer processors described with reference to FIGS. 1, 6A and 6B. As another example, one or more acts of process 200 can be executed using one or more servers (e.g., servers included as a part of a cloud computing

environment). For example, at least a portion of act 210 relating to training of a statistical model (e.g., a neural network) can be performed using a cloud computing environment.

The training process begins at act 202, where sensor signals are obtained for user(s) performing one or more movements (e.g., typing on a keyboard). The sensor signals may be recorded as part of the training process 200, or may be recorded prior to the process and accessed at act 202.

The sensor signals may include sensor signals recorded for a single user performing a single movement or multiple movements. The user may be instructed to perform a sequence of movements for a particular task (e.g., opening a door) and sensor signals corresponding to the user's movements may be recorded as the user performs the task he/she was instructed to perform. The sensor signals can be recorded by any suitable number of sensors located in any suitable location(s) to detect the user's movements that are relevant to the task performed.

For example, after a user is instructed to perform a task with the fingers of his/her right hand, the sensor signals may be recorded by multiple neuromuscular sensors circumferentially (or otherwise) arranged around the user's lower right arm to detect muscle activity in the lower right arm that give rise to the right hand movements and IMU sensors arranged to predict the joint angle of the user's arm relative to the user's torso. As another example, after a user is instructed to perform a task with his/her leg (e.g., to kick an object), sensor signals may be recorded by multiple neuromuscular sensors circumferentially (or otherwise) arranged around the user's leg to detect muscle activity in the leg that give rise to the movements of the foot and IMU sensors arranged to predict the joint angle of the user's leg relative to the user's torso.

The sensor signals obtained in act 202 correspond to signals from one type of sensor (e.g., IMU sensors or neuromuscular sensors). A statistical model may be trained based on the

sensor signals recorded using the particular type of sensor, resulting in a sensor-type specific trained statistical model. For example, the obtained sensor signals may include neuromuscular sensor signals arranged around the lower arm or wrist of a user and the statistical model may be trained to predict musculoskeletal position information for movements of the wrist and/or hand during performance of a task such as grasping and twisting an object such as a doorknob.

In configurations that provide predictions based on multiple types of sensors (e.g., IMU sensors, EMG sensors, MMG sensors, SMG sensors), a separate statistical model is trained for each of the types of sensors and the outputs of the sensor-type specific models are combined to generate a musculoskeletal representation of the user's body. In some configurations, the sensor signals obtained in act 202 from two or more different types of sensors are provided to a single statistical model that is trained based on the signals recorded from the different types of sensors. In an example, an IMU sensor and a plurality of neuromuscular sensors are arranged on a wearable device configured to be worn around the forearm of a user, and signals recorded by the IMU and neuromuscular sensors are collectively provided as inputs to a statistical model, as discussed in more detail below.

The sensor signals obtained in act 202 are recorded at multiple time points as a user performs one or multiple movements. As a result, the recorded signal for each sensor may include data obtained at each of multiple time points. Assuming that n sensors are arranged to simultaneously measure the user's movement information during performance of a task, the recorded sensor signals for the user includes a time series of K n -dimensional vectors $\{\mathbf{x}_k \mid 1 \leq k \leq K\}$ at time points t_1, t_2, \dots, t_K during performance of the movements.

A user may be instructed to perform a task multiple times and the sensor signals and position information may be recorded for each of multiple repetitions of the task by the user. The

sensor signals may include signals recorded for multiple users, each of the multiple users performing the same task one or more times. Each of the multiple users may be instructed to perform the task and sensor signals and position information corresponding to that user's movements may be recorded as the user performs (once or repeatedly) the task he/she was instructed to perform. When sensor signals collected from multiple users are combined to generate a statistical model, an assumption is that different users employ similar musculoskeletal positions to perform the same movements. Collecting sensor signals and position information from a single user performing the same task repeatedly and/or from multiple users performing the same task one or multiple times facilitates the collection of sufficient training data to generate a statistical model that can accurately predict musculoskeletal position information associated with performance of the task.

A user-independent statistical model may be generated based on training data corresponding to the recorded signals from multiple users, and as the system is used by a user, the statistical model is trained based on recorded sensor data such that the statistical model learns the user-dependent characteristics to refine the prediction capabilities of the system for the particular user.

The sensor signals may include signals recorded for a user (or each of multiple users) performing each of multiple tasks one or multiple times. For example, a user may be instructed to perform each of multiple tasks (e.g., grasping an object, pushing an object, and pulling open a door) and signals corresponding to the user's movements may be recorded as the user performs each of the multiple tasks he/she was instructed to perform. Collecting such data facilitates developing a statistical model for predicting musculoskeletal position information associated with multiple different actions that may be taken by the user. For example, training data that

incorporates musculoskeletal position information for multiple actions may facilitate generating a statistical model for predicting which of multiple possible movements a user may be performing.

As discussed above, the sensor data may be obtained by recording sensor signals as each of one or multiple users performs each of one or more tasks one or more multiple times. As the user(s) perform the task(s), position information describing the spatial position of different body segments during performance of the task(s) is obtained in act 204. In some configurations, the position information is obtained using one or more external devices or systems that track the position of different points on the body during performance of a task.

For example, a motion capture system, a laser scanner, a device to measure mutual magnetic induction, or some other system configured to capture position information may be used. In an example, position sensors may be placed on segments of the fingers of the right hand and a motion capture system may be used to determine the spatial location of each of the position sensors as the user performs a task such as grasping an object. The sensor data obtained may be recorded simultaneously with recording of the position information. In this example, position information indicating the position of each finger segment over time as the grasping motion is performed is obtained.

Next, process 200 proceeds to act 206 (optional), where the sensor signals and/or the position information obtained are processed. For example, the sensor signals or the position information signals may be processed using amplification, filtering, rectification, or other types of signal processing.

Next, process 200 proceeds to act 208, where musculoskeletal position characteristics are determined based on the position information. In some configurations, rather than using recorded

spatial (e.g., x , y , z) coordinates corresponding to the position sensors as training data to train the statistical model, a set of derived musculoskeletal position characteristic values are determined based on the recorded position information, and the derived values are used as training data for training the statistical model.

For example, using information about the constraints between connected pairs of rigid segments in the articulated rigid body model, the position information may be used to determine joint angles that define angles between each connected pair of rigid segments at each of multiple time points during performance of a task. Accordingly, the position information may be represented by a vector of n joint angles at each of a plurality of time points, where n is the number of joints or connections between segments in the articulated rigid body model.

Next, process 200 proceeds to act 210, where the time series information obtained (at acts 202 and 208) is combined to create training data used for training a statistical model. The obtained data may be combined in any suitable way. For example, each of the sensor signals may be associated with a task or movement within a task corresponding to the musculoskeletal position characteristics (e.g., joint angles) determined based on the positional information recorded as the user performed the task or movement. In this way, the sensor signals may be associated with musculoskeletal position characteristics (e.g., joint angles) and the statistical model may be trained to predict that the musculoskeletal representation will be characterized by particular musculoskeletal position characteristics between different body segments when particular sensor signals are recorded during performance of a particular task.

Next, process 200 proceeds to act 212, where a statistical model for predicting musculoskeletal position information is trained using the generated training data. The statistical model being trained takes as input a sequence of data sets each of the data sets in the sequence

comprising an n -dimensional vector of sensor data. The statistical model provides output that indicates, for each of one or more tasks or movements performed by a user, the likelihood that the musculoskeletal representation of the user's body will be characterized by a set of musculoskeletal position characteristics (e.g., a set of joint angles between segments in an articulated multi-segment body model).

For example, the statistical model may take as input a sequence of vectors $\{\mathbf{x}_k \mid 1 \leq k \leq K\}$ generated using measurements obtained at time points t_1, t_2, \dots, t_K , where the i th component of vector \mathbf{x}_j is a value measured by the i th sensor at time t_j and/or derived from the value measured by the i th sensor at time t_j . In another example, a derived value provided as input to the statistical model may comprise features extracted from the data from all or a subset of the sensors at and/or prior to time t_j . Based on such input, the statistical model may provide output indicating, a probability that a musculoskeletal representation of the user's body will be characterized by a set of musculoskeletal position characteristics. For example, the statistical model may be trained to predict a set of joint angles for segments in the fingers in the hand over time as a user grasps an object. In this example, the trained statistical model may output, a set of predicted joint angles for joints in the hand corresponding to the sensor input.

In implementations, the statistical model may be a neural network, e.g. a recurrent neural network. The recurrent neural network may be a long short-term memory (LSTM) neural network or any other suitable architecture. For example, the recurrent neural network may be a fully recurrent neural network, a recursive neural network, a variational autoencoder, a Hopfield neural network, an associative memory neural network, an Elman neural network, a Jordan neural network, an echo state neural network, a second order recurrent neural network, and/or any other suitable type of recurrent neural network. Neural networks that are not recurrent neural

networks can also be used. For example, deep neural networks, convolutional neural networks, and/or feedforward neural networks, may be used.

When the statistical model is a neural network, the output layer of the neural network may provide a set of output values corresponding to a respective set of possible musculoskeletal position characteristics (e.g., joint angles). In this way, the neural network operates as a non-linear regression model configured to predict musculoskeletal position characteristics from raw or pre-processed sensor measurements. Any other suitable non-linear regression model can be used instead of a neural network.

The neural network can be implemented based on a variety of topologies and/or architectures including deep neural networks with fully connected (dense) layers, Long Short-Term Memory (LSTM) layers, convolutional layers, Temporal Convolutional Layers (TCL), or other suitable type of deep neural network topology and/or architecture. The neural network can have different types of output layers including output layers with logistic sigmoid activation functions, hyperbolic tangent activation functions, linear units, rectified linear units, or other suitable type of nonlinear unit. Likewise, the neural network can be configured to represent the probability distribution over n different classes via, for example, a softmax function or include an output layer that provides a parameterized distribution e.g., mean and variance of a Gaussian distribution.

Other types of statistical models such as a hidden Markov model, a Markov switching model with the switching allowing for toggling among different dynamic systems, dynamic Bayesian networks, and/or any other suitable graphical model having a temporal component can be used. Such statistical models may be trained using the sensor data.

Values for parameters of the statistical model may be estimated from the training data

generated at act 210. For example, when the statistical model is a neural network, parameters of the neural network (e.g., weights) may be estimated from the training data. For example, parameters of the statistical model may be estimated using gradient descent, stochastic gradient descent, and/or any other suitable iterative optimization technique. When the statistical model is a recurrent neural network (e.g., an LSTM), the statistical model may be trained using stochastic gradient descent and backpropagation through time. The training may employ a cross-entropy loss function and/or any other suitable loss function.

Next, process 200 proceeds to act 214, where the trained statistical model is stored. The trained statistical model may be stored using any suitable. In this way, the statistical model generated during execution of process 200 may be used at a later time, for example, to predict musculoskeletal position information (e.g., joint angles) for a given set of input sensor data, as described below.

Sensor signals may be recorded from sensors (e.g., arranged on or near the surface of a user's body) that record activity associated with movements of the body during performance of a task. The recorded signals may be optionally processed and provided as input to a statistical model trained using techniques described above in connection with FIG. 2. In configurations that continuously record autonomous signals, the continuously recorded signals (raw or processed) may be continuously or periodically provided as input to the trained statistical model for prediction of musculoskeletal position information (e.g., joint angles) for the given set of input sensor data. As discussed above, the trained statistical model is a user-independent model trained based on autonomous sensor and position information measurements from a plurality of users. In some configurations, the trained model is a user-dependent model that is trained on data recorded from the individual user from which the data associated with the sensor signals is also acquired.

After the trained statistical model receives the sensor data as a set of input parameters, the predicted musculoskeletal position information is output from the trained statistical model. The predicted musculoskeletal position information includes a set of musculoskeletal position information values (e.g., a set of joint angles) for a multi-segment articulated rigid body model representing at least a portion of the user's body. In some examples, the musculoskeletal position information includes a set of probabilities that the user is performing one or more movements from a set of possible movements.

After musculoskeletal position information is predicted, a computer-based musculoskeletal representation of the user's body is generated based on the musculoskeletal position information output. The computer-based musculoskeletal representation may be generated in any suitable way. For example, a computer-based musculoskeletal model of the human body may include multiple rigid body segments, each of which corresponds to one or more skeletal structures in the body. For example, the upper arm may be represented by a first rigid body segment, the lower arm may be represented by a second rigid body segment the palm of the hand may be represented by a third rigid body segment, and each of the fingers on the hand may be represented by at least one rigid body segment (e.g., at least fourth- eighth rigid body segments).

A set of joint angles between connected rigid body segments in the musculoskeletal model may define the orientation of each of the connected rigid body segments relative to each other and a reference frame, such as the torso of the body. As new sensor data is measured and processed by the statistical model to provide new predictions of the musculoskeletal position information (e.g., an updated set of joint angles), the computer-based musculoskeletal representation of the user's body is updated based on the updated set of joint angles determined

based on the output of the statistical model. In this way, the computer-based musculoskeletal representation is dynamically updated, e.g., in real-time, as sensor data is continuously recorded.

The computer-based musculoskeletal representation may be represented and stored in any suitable way. Additionally, although referred to herein as a “musculoskeletal” representation, to reflect that muscle activity may be associated with the representation, as discussed in more detail below, some musculoskeletal representations may correspond to skeletal structures, muscular structures, or a combination of skeletal and muscular structures in the body.

Direct measurement of neuromuscular activity and/or muscle activity underlying the user’s movements may be combined with the generated musculoskeletal representation. Measurements from sensors placed at locations on a user’s body may be used to create a unified representation of muscle recruitment by superimposing the measurements onto a dynamically-posed skeleton. Muscle activity sensed by neuromuscular sensors and/or information derived from the muscle activity (e.g., force information) can be combined with the computer-generated musculoskeletal representation in real time.

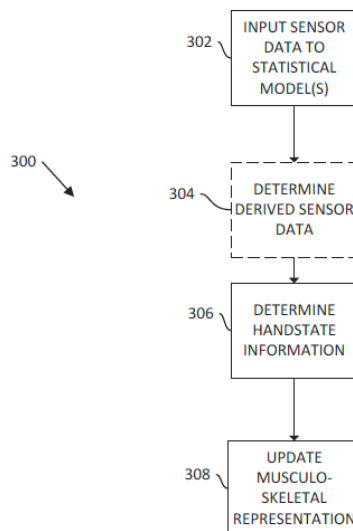


Fig. 3

FIG. 3 is a flowchart of an example process for determining handstate information . In act 302, sensor data recorded by the sensors is provided as input to one or more trained statistical models used to generate estimates of handstate information, as described briefly above. The sensors can include a plurality of neuromuscular sensors (e.g., EMG sensors) arranged on a wearable device worn by a user. For example, one or more types of neuromuscular sensors may be arranged on an elastic band configured to be worn around a wrist or forearm of the user to record neuromuscular signals from the user as the user performs various movements or gestures.

As used herein, the term “gestures” refers to a static or dynamic configuration of one or more body parts including the position of the one or more body parts and forces associated with the configuration. For example, gestures include discrete gestures, such as pressing the palm of a hand down on a solid surface or grasping a ball, continuous gestures, such as a waving a finger back and forth or throwing a ball, or a combination of static and continuous gestures. Gestures may be defined by an application configured to prompt a user to perform the gestures or, alternatively, gestures may be arbitrarily defined by a user. In some cases, hand and arm gestures may be symbolic and used to communicate according to cultural standards.

In addition to neuromuscular sensors, some configurations include one or more auxiliary sensors configured to continuously record auxiliary signals that may also be provided as input to the one or more trained statistical models. Examples of auxiliary sensors include IMU sensors, imaging devices, radiation detection devices (e.g., laser scanning devices), heart rate monitors, or any other type of biosensors configured to continuously record biophysical information from the user during performance of one or more movements or gestures.

Process 300 then proceeds to act 304, where derived signal data is optionally determined based on the signals recorded by the sensors. For example, accelerometer data recorded by one

or more IMU sensors is integrated and/or filtered to determine derived signal data associated with one or more muscles during performance of a gesture. The derived signal data may be provided as input to the trained statistical model(s) in addition to or as an alternative to raw signal data or otherwise processed raw signal data recorded by the sensors.

Process 300 then proceeds to act 306, where handstate information is determined based on the output of the trained statistical model(s). The gestures performed by the user include discrete gestures, such as placing the hand palm down on a table, and continuous gestures, such as waving a finger back and forth. The neuromuscular signals are recorded continuously during user movements including during performance of the gesture and are provided continuously as input to the trained statistical model, resulting in real-time estimation of the positions and/or forces of the user's hand (i.e., handstate information) as output of the trained statistical model(s).

Process 300 then proceeds to act 308, where the real-time handstate estimates output from the trained statistical model(s) are used to update a musculoskeletal representation associated with a hand. The musculoskeletal representation may represent rigid segments within a hand and the joints connecting the rigid segments. The musculoskeletal representation may include at least some rigid segments corresponding to an arm connected to the hand. Accordingly, the phrase “musculoskeletal representation associated with hand” is to be understood to include both musculoskeletal representations of the hand and musculoskeletal representations that include a representation of the hand and at least a portion of an arm connected to the hand.

Existing touchscreen interfaces are able to recognize when a portion of a user's body touches it – such as when a finger makes contact with the sensor, as well as the finger's position and some other basic information such as the force applied onto the touchscreen by the finger.

However, human hands and fingers (for example) exhibit much higher degrees of freedom. For example, a user may use a specific finger (e.g., index, middle, ring, pinky, thumb) to contact the touchscreen, all of which are generally recognized as the same touch interaction by the touchscreen sensor and associated software. Moreover, a user may, for example, form a fist and use the side of the hand to interact with the screen (i.e. by ‘wiping’ something via the touchscreen). Furthermore, current touchscreen sensors and associated software are generally unable to determine the orientation of the hand or finger as the user approaches or touches the device.

Fusing touchscreen systems with neuromuscular data from a user’s arm or wrist (along with statistical models and/or other data processing routines that determine the posture, gestures, forces, and/or handstate of the user) can address at least some of the limitations of touchscreen systems described above. Techniques that fuse touchscreen systems with neuromuscular data (obtained via statistical models as described herein) can improve touchscreen sensor systems for machine control. Such techniques enable identification of which finger or fingers are interacting with the touchscreen permitting the use of finger-specific interaction frameworks that significantly extend the capabilities of current touchscreen systems.

For example, fusion of neuromuscular and touchscreen data may enable a user to draw in one color with her index finger and draw in another color with her middle finger. The conventional touchscreen recognizes a finger interaction with the touchscreen in both cases but is not able to distinguish them. By fusing neuromuscular data with the touchscreen data, and further incorporating statistical models for inferring handstate based on neuromuscular data (as described herein), the described techniques enable expanded functionality of interactions that are natural and simple to learn. In another example, the handstate of the user may be determined to

be in a fist such that any interaction with the touchscreen enables an erasing function. The fusion of touchscreen and neuromuscular data (including estimating handstate, poses, or forces) enables a deeper set of interactions for various computer applications.

Fusion of neuromuscular and touchscreen data may be configured to recognize the pose of a hand of the user at the time the user makes contact with the touchscreen. For example, is the user pointing with one or more fingers, in an open palm posture, making a fist, etc. Each different hand position, posture, force, or handstate can be used to control a distinct form of interaction once the user touches the touchscreen, thereby significantly extending the control schemes possible via a touchscreen. Further, fusion of neuromuscular and touchscreen data may be used to recognize the yaw, pitch, and roll of a finger as it makes contact with the touchscreen and thereby use the finger position relative to the touchscreen to affect the machine control effected by touchscreen interaction. Currently, some styluses make use of this type of orientation information to modulate a drawing tool; however, doing so purely with a finger is not possible with a conventional touchscreen alone.

A device that fuses neuromuscular and touchscreen data may be configured to more accurately estimate the force with which a user is interacting with a touchscreen, permitting machine control schemes based on this force information. Although some touch sensors make a rough estimate about how hard a user is pressing against the screen (commonly "force" or "pressure"), this information can be made more accurate by incorporating neuromuscular data and statistical models derived from neuromuscular data that are configured to estimate force.

The fusion of neuromuscular and touchscreen data may be utilized to inform palm rejection (determine which touchscreen interactions to ignore/cancel). Conventional touch sensor drivers often look for touches that start small and then become big blobs, then classify these

interactions as ‘palms’, then cancel the input. The rationale of such touchscreen systems is that the user is resting their hand on the screen and thus, didn’t intend to supply input. This feature of touchscreens leads to both false positive and false negatives. By fusing touchscreen and neuromuscular data, the described techniques can supply enough "hand resting" information in order to determine if a particular touch is a palm or not.

Moreover, many touchscreen systems enable ‘multitouch’ interactions where two fingers touching the touchscreen cause a different control input than a single finger. In such computer applications, collaborative touchscreen interaction is difficult because the touchscreen cannot readily distinguish between two fingers from one user and a pair of fingers from two users.

Any suitable number of neuromuscular sensors may be used on a wearable device. The number and arrangement of neuromuscular sensors may depend on the particular application for which the wearable device is used. For example, a wearable armband or wristband can be used to generate control information for controlling a touch screen or a device connected to the touch screen.

In some configurations, sensors include a set of neuromuscular sensors (e.g., EMG sensors). In some configurations, sensors can include a set of neuromuscular sensors and at least one “auxiliary” sensor configured to continuously record auxiliary signals. Some examples of auxiliary sensors include other sensors such as IMU sensors, microphones, imaging sensors (e.g., a camera), radiation based sensors for use with a radiation-generation device (e.g., a laser-scanning device), or other types of sensors such as a heart-rate monitor. The sensors may be coupled together using flexible electronics incorporated into the wearable device.

CONCLUSION

This disclosure describes techniques to determine handstate by the use of a wearable device with built-in sensors. A statistical model is trained using training data that includes sensor readings known to be associated with various hand poses and gestures. The trained statistical model is configured to determine handstates based on sensor readings. In implementation, a distributed system includes a touchscreen interface adapted to receive one or more touchscreen inputs and a component coupled to the touchscreen interface that receives neuromuscular data from a user. The component provides control signals to the touchscreen interface based on the received neuromuscular data.. For example, the handstates can include identification of a portion of the hand that is interacting with the touchscreen, a user's finger position relative to the touchscreen, an identification of which finger or fingers of the user's hand are interacting with the touchscreen, etc. The determined handstate can be used to control the touchscreen or a device connected to the touchscreen.